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Does Air Pollution Cause Obesity? New Evidence from China

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Abstract: The global obesity rate has risen at an alarming rate in recent decades, and "fatness" has become an increasingly serious public health problem. At the same time, the loss of working hours and increased medical costs caused by air pollution have a wide range of direct and indirect effects on the health of the population and the macroeconomy. Against this background, using data from the China Family Panel Survey and thermal inversion as instrumental variables, this study analyzes the effect of air pollution on the risk of obesity among residents. We employ a two-stage least squares method to identify the effects of air pollution on the risk of obesity. The findings indicate that for a 1 μg/m^3 increase in the annual average $PM_{2.5}$ concentration at the county level, the obesity level increases significantly by 0.0286. This result is credible after a series of robustness checks; male groups, less-educated groups, and rural residents are more sensitive to the negative effects of air pollution. Finally, policy suggestions are provided.

Keywords: air pollution, obesity, instrumental variable, thermal inversion

1. Introduction

Obesity, the pathological accumulation of adipose tissue, poses a grave threat to human well-being. In China, a marked disequilibrium between energy intake and expenditure has engendered a notable upswing in the prevalence of overweight and obesity. The report on *Nutrition and Chronic Diseases of the Chinese Population* (2020) reveals that the rates of adult overweight and obesity are 34.3% and 16.4%, respectively. The scourge of obesity has emerged as one of the top 10 chronic diseases in China, exacting a deleterious toll on national progress (Caterson et al., 2019; Luyckx et al., 2021; Popkin & Ng, 2022). Overweight and obesity represent well-established risk factors for a range of chronic non-communicable diseases, including cardiovascular disease, kidney disease, diabetes, and cancer. In 2019, deaths attributed to overweight, and obesity accounted for a staggering 11.1% of all deaths from chronic non-communicable diseases, a significant increase from the 5.7% recorded in 1990. This upward trend is of grave concern, given that the rising cost of obesity in terms of medical resources is already presenting a formidable challenge to improving quality of life. Furthermore, increasing rates of overweight and obesity may lead to a loss of human resources, as some working-age individuals may lose their jobs or even their lives due to the health complications associated with this condition.

To deal with the risk of obesity and the resulting public problems, many scholars are investigating the factors that lead to obesity from all possible aspects. Hou et al. (2021) find that obesity contributes to the occurrence of hypertension at high concentrations of air pollutants, which further suggests that in obese individuals, exposure to air pollution increases the total blood volume, heart output, and volume of blood discharged into the blood vessels per minute, thus leading to associated hypertension and epidemic hypertensive disorders. Muscogiuri et al. (2020) provide the observational evidence on the risk of obesity and somnolence. They discussed the mechanisms of both pathologies from a physiological perspective, including hormones and metabolism. Many studies have attempted to understand obesity based on economic factors such as income (Akee et al., 2013; Cawley et al., 2015), education (Clark & Royer, 2013), and peer and neighbor effects (Kling et al., 2007).

However, very few studies analyze obesity from the perspective of air pollution. Therefore, this study attempted to examine the potential factors of obesity from an environmental perspective, specifically that of air pollution.

According to the International Standardization Organization definition, air pollution refers to the fact that when the concentration of a substance in the air exceeds a certain level, it damages the ecosystem and normal living and development conditions of human beings. The World Health Organization (2021) states that air pollution kills approximately seven million people worldwide every year. Air pollution affects a wide range of people. In children, it can affect lung development, impair lung function, and cause respiratory infections. In adults, it can cause strokes and ischemic heart disease. There is growing evidence of a causal link between air pollution and cardiovascular disease

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(de Oliveira Alves et al., 2017; Gilmour et al., 2001; Prabhakaran et al., 2018).

Apart from the health viewpoint, air pollution is a major environmental problem, causing substantial negative effects on human society. A significant body of research examines all kinds of negative effects caused by air pollution. Studies have established that economic losses and health risks resulting from air pollution are immeasurable.

Air pollution has a multitude of adverse effects. First, it has been shown to increase anxiety levels, leading to a rise in crime and immorality (Lu et al., 2018). Second, there exists an inverted U-shaped relationship between air pollution and labor productivity, whereby productivity initially increases with pollution but then decreases as pollution levels continue to rise (He et al., 2019). Third, air pollution has a significant negative impact on individual subjective well-being, primarily through physical health, physical exercise behavior, and obesity (Zhang et al., 2022). Finally, the loss of labor and increased medical costs caused by air pollution have far-reaching direct and indirect impacts on both health and macroeconomic production (Chen & Bloom, 2019). Given that obesity is a key indicator of health and can also have significant implications for macroeconomic production, it is crucial to understand the link between air pollution and obesity, as well as to recognize the potential health risks associated with air pollution. By doing so, individuals and countries can become more aware of the issue and take positive measures to address it. In addition, Deschenes et al. (2020), who link air pollution data with individual-level overweight and obesity rates and find that air pollution had a significant positive effect on weight gain, are the most relevant study to ours.

This study utilizes China Family Panel Survey (CFPS) data to conduct empirical analysis that accurately captures individual characteristics and the external environment of the respondents, including obesity risk, overweight status, and contemporaneous air quality and weather conditions. The data of 12,688 respondents from 2010 to 2018 are collected to measure the obesity risk and overweight situation. To address the endogeneity issue in existing research on air pollution and obesity risk, we use thermal inversion as an instrumental variable (IV) and build a two-stage least squares (2SLS) econometric model to identify the casual effect of air pollution on obesity risk.

The contribution of this study is twofold. On one hand, it is one of the earliest empirical investigations to explore the incidental effect of air pollution on obesity risk in the largest developing country from a micro individual perspective. Deschenes et al. (2020) provided the groundwork for our research. One key distinction between our study and theirs lies in our use of CFPS data, which is more detailed, extensive, and dependable than the data set they utilized, the China Health and Nutrition Survey. Moreover, our work adds to the body of health literature by employing rigorous identification design techniques to explore the perceived value of thermal inversion using IV methods.

The remainder of this paper is organized as follows. The theoretical mechanism and model specification are introduced in Section 2. Data and statistics of variables are presented in Section 3. The basic results of our empirical investigations, robustness checks, and heterogeneous effects are summarized in Section 4. Finally, conclusions and policy suggestions are provided in Section 5.

2. Mechanisms

Studies have established that air pollution may contribute to obesity through several pathways. First, air pollution can lead to metabolic disorders in humans. Second, it affects weight by increasing the risk of chronic diseases (An et al., 2018). Third, sleep quality is often affected, which in turn affects their appearance (Heyes & Zhu, 2019). Finally, because of air pollution, people tend to exercise less outside and stay indoors, which indirectly leads to the accumulation of fat (Laumbach & Cromar, 2022).

Although previous health studies have suggested a possible link between air pollution and obesity, establishing a causal relationship between the two is difficult due to the requirement for precise measurement of overweight and obesity. To mitigate endogeneity concerns, the use of thermal inversion as an IV has become increasingly prevalent in recent years. In a typical atmospheric phenomenon, the temperature of the air close to the surface is higher than that of the upper layer. However, if the air temperature near the surface is lower than the temperature in the upper layer, a thermal inversion phenomenon occurs. In this case, air mobility is poor, and the concentration of air pollutants at ground level is unable to disperse effectively; the result is an accumulation of air pollution in the region. Environmental economists have used thermal inversion to investigate the economic (Fu et al., 2021) and health effects (Deschenes et al., 2020) of air pollution.

Our results in identifying causal relationships between air pollution and obesity risk are affected by two major challenges. Because there is a strong link between air pollution and the level of economic development of an area, the first challenge is that there may be a potential problem of omitted variables. For example, more economically developed regions tend to have more severe air pollution problems. Economic development affects the income and dietary habits of residents, and these factors also affect weight. Additional income can either increase or decrease weight. Lakdawalla et al. (2005) determined an inverted U-shaped relationship between income and weight. Additionally, owing to differences in habits and financial ability, respondents will alter where they live based on where they want to live, which in turn changes their external contact environment. The respondents' initiative to change their place of residence due to the impact of air pollution may also lead to the problem of omitted variables. The second challenge is the data measurement error. Data on air pollution concentration can be artificially modified as needed, especially in developing countries. Therefore, instead of using the official Chinese government data directly, we use more accurate data. In addition, thermal inversion has a strong correlation with air pollution, but none with economic activity (Arceo et al., 2016). At both county and national levels, economic output has been proven to be largely indifferent to the absence of inversion (Deschenes et al., 2020). Therefore, thermal inversion fully meets the requirements as an IV of air pollution.

3. Empirical model and data explanation

3.1. Econometric model

By controlling for meteorological conditions, we made the thermal inversion meet the exclusion restriction criterion of IVs, that is, thermal inversion can only affect the degree of obesity through air pollution. We selected thermal inversion as an IV for air pollution for two primary reasons. First, there is a strong correlation between thermal inversion and air pollution. Thermal inversion causes warm air to remain close to the ground, leading to temperature inversion that restricts the upward movement and convection of air, impeding the diffusion and dilution of pollutants in the atmosphere, thereby worsening air quality. As a result, there is a positive relationship between thermal inversion and air pollution, with greater thermal inversion generally indicating more severe air pollution.

Second, the occurrence of thermal inversion is not found to be correlated with other endogenous variables within the model. Endogeneity refers to a scenario wherein a variable is impacted by other endogenous variables, potentially leading to biased estimation results. However, thermal inversion is usually an exogenous variation, triggered by meteorological conditions and not influenced by economic decision-makers or other endogenous variables, such as levels of economic activity or population distribution. Therefore, thermal inversion can be regarded as an exogenous IV that does not induce endogeneity bias.

Based on these two key reasons, this paper constructs an empirical strategy for IV and proposes the following 2SLS model to estimate the causal effect of air pollution on the degree of obesity.

$$Y_{ict} = \varphi_0 + \varphi_1 Air_{ict} + \beta X'_{ict} + \gamma W'_{ict} + \lambda_i + \mu_t + \varepsilon_{ict} \quad (1)$$

$$Air_{ict} = \theta_0 + \theta_1 Ti_{ict} + \beta X'_{ict} + \gamma W'_{ict} + \lambda_i + \mu_t + \pi_{ict} \quad (2)$$

where Y_{ict} represents the obesity indicator for respondent *i* residing in county *c* at date *t*. We used the average annual $PM_{2.5}$ concentration as an explanatory variable. Equation (2) is the first-stage estimate of the least squares in two stages to investigate the impact of the cumulative number of thermal inversion Ti_{ict} on the level of air pollution Air_{ict}. Equation (1) is the second-stage estimate of the least squares in two stages to investigate the impact of air pollution Air_{icr} on the risk of obesity Y_{ict}. In addition, considering that weather factors not only affect our IVs but also may have a significant impact on the risk of obesity, we added a wealth of weather conditions W'_{ict} into the 2SLS model, including daily average, minimum and maximum temperature, wind speed and direction, precipitation, and sunshine number, etc. The set of individual-level controls, denoted as X'_{ict}, comprises various demographic variables, such as age, health, education, employment status, marital status, household registration, insurance, income, and social status. A detailed definition of these variables is provided in the summary statistics table presented later in this paper. Ti_{ict} is our IV, representing the number of thermal inversion in county *c* of the respondent *i* in year *t*. More importantly, λ_i represents individual fixed effects, which can exclude the impacts of individual-level factors that do not change over time among respondents, such as gender and geographical location. μ_t represents the year fixed effects and controls the impacts of macro-level factors that do not change with individuals, such as the increasing concern of residents about body fat caused by the Healthy China Strategy proposed by the Chinese government; ε_{ict} and π_{ict} are error terms.

3.2. Data

3.2.1. Obesity data

At present, body mass index (BMI) is commonly employed widely to assess the degree of obesity and health status. BMI is calculated by dividing the weight of a person (kg) by the square of their height (m). In this paper, the WHO standard is used to measure the degree of obesity and thinness. People are considered obese if their BMI exceeds 30.

First of all, the CFPS questionnaire has a special section asking the respondent's height and weight, so we can directly calculate the corresponding BMI. Apart from that, the CFPS questionnaire included information on the location and date of the respondents, allowing us to precisely match individual obesity levels with local annual air pollution levels. Finally, it is worth noting that the CFPS questionnaire includes a range of multidimensional indicators, such as income, education, physical health, and various other relevant factors (with a focus on variables related to individual obesity based on real-world observations). This extensive coverage enables us to incorporate a broad set of control variables in our estimations, thus enhancing the robustness and accuracy of our analysis.

3.2.2. Air pollution data

We use $PM_{2.5}$ concentration to represent the severity of regional air pollution. In the existing paper, most authors directly use air pollution data provided by ground monitoring stations of the National Environmental Monitoring Center of the Ministry of Environmental Protection of China. Although the data are fairly accurate, it is very expensive to detect. Due to the limited number and uneven distribution of detection platforms, regional air pollution detection also has some limitations of distribution in China. Due to policy needs, there is the possibility of artificial tampering with the data. In order to eliminate the above limitation and calculate the near-surface $PM_{2.5}$ concentration, we use the aerosol optical depth (AOD) data from satellites. Basically, AOD represents an integral of absorbance of vertical air column concentration that has a high relationship with ground-level particles. According to the research method of Buchard et al. (2016), we obtained the latitude and longitude grid data of AOD (0.5° × 0.625°, about 50 km × 60 km) since 1980 from the modern retrospective analysis of NASA Research and Applications Second Edition (MERRA-2). Using Arcgis10.2 software and following their methods, spatial grid data on $PM_{2.5}$ concentrations were computed for China from 2010 to 2018, and annual air pollution data were aggregated to the county level. Furthermore, the SO_2 concentration data from NASA allowed us to further conduct robustness checks regarding SO_2 as a proxy for air pollution.

3.2.3. Thermal inversion data

The thermal inversion data were obtained from NASA's MERRA-2 satellite imagery product. The MERRA-2 satellite image is a global space raster and provides temperature data for every 6 h since 1980 in a 50*60 km grid with an altitude difference of 42 atmosphere from 110 to 36,000 m above sea level, and we then aggregated the data from each level for each year to the county level. Under normal atmospheric conditions, temperatures in the upper layers are lower than those near the surface. But if the temperature of the first layer (110 m) close to ground is lower than that of the second layer (320 m), the thermal inversion phenomenon is considered to occur. At this time, due to the poor air mobility, pollutants near the ground could not volatilize efficiently, which aggravated the severity of air pollution near the ground in this area. Because the MERRA-2 satellite data provide average temperature data every 6 h, we can judge whether this phenomenon occurs four times in a day. To unify the assessment standard and reduce measurement error, we defined the thermal inversion that occurred at least once in the same day in the county as inversion.

3.2.4. Meteorological station data

We obtain the necessary meteorological information from the National Meteorological Centre of China and monitor daily average, minimum and maximum temperatures, wind speed, wind direction, and sunshine hours from over 800 weather stations. We also refer to the inverse distance weight method (Deschenes et al., 2020) and convert the data from the weather station to the county level with a radius of 200 km.

3.3. Variable statistics

Table 1 summarizes the key variables of the empirical study in this paper. In our sample, the mean value for obesity is 0.639 and the standard deviation is 0.48. Air pollution data, thermal inversion data, and weather conditions are all county-level annual data. Specifically, the average concentration of $PM_{2.5}$ from 2010 to 2018 is 72.44 μg/m³, more than seven times the health standard of 10 μg/m³ recommended by the World Health Organization, with a standard deviation of 31.18.

4. Results

4.1. OLS result

First of all, we do not introduce IVs and run Ordinary Least Squares (OLS) regression results directly, as shown in equation (1). Table 2 shows the regression results of OLS, indicating that no effect of air pollution on the risk of obesity is found in all regressions regardless of whether controlling individual variables or weather variables. This regression result just proves the above analysis. Due to the existence of the endogeneity problem of air pollution, our measurement will be biased. After considering the problems of measurement bias and two major challenges in the OLS model, we further introduced the 2SLS model to more precisely analyze the effect of air pollution on the risk of obesity.

4.2. SLS result

4.2.1. First-stage results

In the first stage, the impact of thermal inversion on air pollution was investigated. The regression results are shown in Table 3. The annual temperature in the county is taken as the explanation variable, and the annual $PM_{2.5}$ pollution degree in the county is the explained variable. The first column of data in the table is the result of the absence of any weather control and individual control. The second and third columns add the weather condition control and individual condition control, respectively, on the basis of the first column, while the fourth column is the strictest condition control, adding the weather condition and individual condition control.

In a word, we found that thermal inversion had a significant positive effect on annual $PM_{2.5}$ concentration at the level of 1%. Therefore, we can confirm that when the thermal inversion phenomenon occurs, the near-ground pollutants are difficult to volatilize effectively, and then the regional air pollution degree is increased. The results in column 4 show the F statistic is 668.32, which is far more than the specified valid stock-yogo value. Besides, the result in the first row is 0.0066, which suggests that at the county level, a thermal inversion could increase the concentration of $PM_{2.5}$ by 0.0066 μg/m³, equivalent to 0.01% of the sample average.

4.2.2. Second-stage results

$PM_{2.5}$ is selected as the key air pollution variable in this paper. The results of regression are shown in Table 4. Column 1 is a simple regression estimate, adding individual and year fixed effects, showing a significant effect of annual average $PM_{2.5}$ concentration on obesity risk at the 1% level. Column 2 added weather controls to column 1 and found that the effect of air pollution on obesity risk is significant at the 1% level. The third column adds individual control variables to the first column and still finds a negative and significant effect of air pollution on the risk of obesity at the 1% level. The fourth

Table 1
Summary statistics

Variable	Definition	Mean	SD	Min	Max
Individual level					
Obesity	If BMI >=30, it is denoted as 1, otherwise it is 0	0.639	0.480	0	1
Age	Individual age	50.45	13.67	16	94
Health	Health status, ranging from 1 to 5, the higher, the better	2.933	1.305	1	5
Education	Education years	6.435	4.741	0	20
Employ	Employment status (0 = Unemployment, 1 = Employment)	0.678	0.467	0	1
Marital status	1 = Single, 2 = Married, 3 = Cohabit, 4 = Divorce, 5 = Widowed	2.148	0.745	1	5
Household registration	0 = Rural household registration, 1 = City household registration	0.443	0.497	0	1
Insurance	Whether to purchase insurance (0 = No, 1 = Yes)	0.914	0.280	0	1
Income	Self-rated satisfaction of income status (1 = Very dissatisfied, 2 = Dissatisfied, 3 = Moderately satisfied, 4 = Satisfied, 5 = Very satisfied)	2.491	1.045	1	5
Social status	Self-evaluation of local social status (1 = Very dissatisfied, 2 = Dissatisfied, 3 = Moderately satisfied, 4 = Satisfied, 5 = Very satisfied)	2.931	1.051	1	5
County level					
$PM_{2.5}$	Annual average $PM_{2.5}$ concentration (μg/m³)	72.44	31.18	7.292	141.6
SO_2	Annual average SO_2 concentration (μg/m³)	26.20	15.12	0.816	63.60
Temperature	Average temperature (Celsius)	14.31	4.701	−0.900	23.70
Humidity	Relative humidity (%)	66.00	9.108	42.40	86
Precipitation	Total precipitation (mm)	946.9	543.0	132.2	3,203
Sunshine	Sunshine hours (hour/year)	1,971	477.0	598.4	3,024
Thermal inversion index I	Number of inversions (day/year)	158.1	77.69	4	324
Thermal inversion index II	Number of inversions (day/year)	112.8	60.69	1	275

Table 2
OLS regression results

	(1)	(2)	(3)	(4)
$PM_{2.5}$ (μg/m³)	0.0006	0.0001	0.0007*	0.0002
	(0.0004)	(0.0005)	(0.0004)	(0.0005)
Age			0.0014	0.0030
			(0.0032)	(0.0051)
Education			−0.0017*	−0.0013
			(0.0010)	(0.0011)
Household registration			−0.0193**	−0.0212**
			(0.0078)	(0.0086)
Marital status			−0.0028	−0.0002
			(0.0036)	(0.0041)
Employ			−0.0048	−0.0030
			(0.0036)	(0.0039)
Health			−0.0015	−0.0019
			(0.0015)	(0.0017)
Insurance			−0.0007	−0.0039
			(0.0052)	(0.0056)
Income			−0.0004	−0.0012
			(0.0016)	(0.0019)
Social status			0.0012	0.0020
			(0.0016)	(0.0018)
Weather controls	NO	YES	NO	YES
Individual fixed effects	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
Observations	63,340	48,812	58,727	45,088

Note: The standard errors are reported in parentheses. *, **, *** indicate different levels of significance (10%, 5%, and 1%), respectively (the same below).

Table 4
Second-stage results: the impacts of air pollution on obesity

	(1)	(2)	(3)	(4)
$PM_{2.5}$ (μg/m³)	0.0165***	0.0342***	0.0154***	0.0286***
	(0.0048)	(0.0095)	(0.0050)	(0.0098)
Age			0.0016	0.0040
			(0.0031)	(0.0052)
Education			−0.0017*	−0.0014
			(0.0010)	(0.0012)
Household registration			−0.0281***	−0.0402***
			(0.0085)	(0.0116)
Marital status			−0.0028	−0.0001
			(0.0038)	(0.0044)
Employ			−0.0026	−0.0015
			(0.0037)	(0.0042)
Health			−0.0007	−0.0011
			(0.0015)	(0.0018)
Insurance			-0.0032	−0.0068
			(0.0053)	(0.0061)
Income			−0.0001	−0.0002
			(0.0016)	(0.0020)
Social status			0.0016	0.0022
			(0.0016)	(0.0019)
Weather controls	NO	YES	NO	YES
Individual fixed effects	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
Observations	63,340	48,812	58,727	45,088

Table 3
First-stage results: the impacts of thermal inversion on air pollution

	(1)	(2)	(3)	(4)
Thermal inversion	0.0107***	0.0071***	0.0102***	0.0066***
	(0.0008)	(0.0009)	(0.0008)	(0.0009)
Individual controls	NO	NO	YES	YES
Weather controls	NO	YES	NO	YES
Individual fixed effects	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
KP F-statistics in first stage	185.87	1981.75	20.92	668.32

column is our preferred specification model, where we add weather controls, individual fixed effects and year fixed effects, and individual control variables. Column 4 shows an increase in average annual $PM_{2.5}$ concentrations of 1 μg/m³ is associated with a significant increase in obesity of 0.0286 (4.48% of mean). Combining the magnitude of this positive effect with the OLS regression results above, we can consider our IV regression results to be reliable. This is due to the fact that we use thermal inversion as an IV of air pollution instead of directly using air pollution index, which effectively overcomes the problems of variable omission, measurement bias, and bidirectional causality in OLS regression.

Deschenes et al. (2020) have reported that 1 μg/m^3 increase in average $PM_{2.5}$ concentrations leads to a 0.31% increase in BMI. Hou et al. (2021) suggest that individuals with high PM_1 concentrations plus obesity classified by BMI had a 4.18-fold (95% CI: 3.86, 4.53) increase in prevalent hypertension compared to non-obese individuals with low PM_1 concentrations; similar findings were observed for the combined effect of $PM_{2.5}$. Notably, the discrepancy in the direct use of BMI as the outcome variable in their research, versus the generation of dummy variables based on whether BMI is greater than 30 in our study, may account for the observed difference in results.

In addition, as shown in column 4 of Table 4, we find that we creatively found that the respondent's household registration had a statistically significant effect on his or her obesity level, with a negative regression coefficient. This suggests that rural residents have a higher risk of obesity. The reason is that with the development of social economy, rural residents have more and more opportunities to contact high-calorie and refined food, and people's nutrition can be supplemented. On the other hand, the development of mechanization allows farmers to reduce the amount of labor so that reduce the loss of heat.

4.3. Robustness checks

We conduct some robustness checks of the above regression results. The robustness check is mainly carried out by three methods: the transformation of air pollution proxy variables, the change of thermal inversion definition, and the addition of irrelevant explained variables for regression analysis.

First, we use the county average annual SO_2 concentration instead of the county average annual $PM_{2.5}$ concentration as a proxy variable for air pollution. SO_2 is a gas with a choking odor that predisposes the human respiratory tract to inflammation, which in turn prevents air from being inhaled into the lungs. High concentrations of sulfur dioxide that make breathing difficult can lead to bronchitis, asthma, emphysema, and even death. In addition, sulfur dioxide has a strong irritating effect on mucous membranes, which can lead to human diseases such as bronchitis, pneumonia, pulmonary edema, and respiratory paralysis. We can see the results in Table 5. The coefficient of the first stage in column 4 is 0.0036, indicating that the occurrence of a thermal inversion will increase the annual county SO_2 concentration by 0.0036 μg/m³. Besides, the F statistic is 174.33, which is much higher than the specified stock-yogo value. Thus, we can know that an increase in the average annual SO_2 concentration of 1 μg/m³(3.82% of mean) is associated with a significant increase in the risk of obesity by 0.0523 (8.18% of mean). The results are qualitatively consistent with those using $PM_{2.5}$ as an air pollution variable.

Apart from that, we further use the new thermal inversion definition for robustness check. The thermal inverse in fact has different definitions, for example, radiation inversion often occurs in the clear and cloudless night sky, due to the ground effective radiation is very strong, the temperature of the near-surface layer drops rapidly, while the higher atmosphere cools less, thus appearing on the warm and cold inverse temperature phenomenon. Stratospheric inversion is warm air moving horizontally to the cold ground or air layer because the lower layer of warm air is affected by the cold ground or air layer and cools rapidly, and the upper layer is less affected and cools more slowly, thus forming inverse temperature. Topographic inversions are mainly caused by topography, mainly in basins and valleys. As the slope of the mountain dissipates heat quickly, the cold air sinks to the bottom of the valley along the slope, and the original warmer air at the bottom of the valley is lifted and squeezed up by the cold air, thus the inversion of temperature occurs. In the previous 2SLS regression, we default that the temperature of the second layer (320 m) is higher than that of the first layer (110m) as a thermal inversion phenomenon. We now set the different altitudes to define thermal inversion. If the temperature in the third layer (540 m) is higher than the temperature in the first layer (110 m), we consider an inversion to have occurred. Table 6 reports the results. In the first and second stages, we found that the relationship between the number of thermal inversion, the degree of air pollution, and the risk of obesity is the same as the previous regression results, except that the coefficients changed. Therefore, we consider the previous regression results to be robust.

In the meantime, we use height as an explanatory variable in the falsification test. This is an individual variable that is totally uncorrelated with air pollution. The results are shown in Table 7, where we find that the effect of air pollution on individual height is statistically insignificant, which in turn confirms the reliability of our results.

4.4. Heterogeneous effects

This paper uses the basic information of the respondents to analyze the heterogeneity of the benchmark results. For example, there are gender differences in lung diseases such as asthma and respiratory infections, and we need to learn more about how women and men cope with air pollution and what this means for

Table 5
2SLS result: using annual average SO_2 concentration as the air pollution variable

	(1)	(2)	(3)	(4)
First stage				
Thermal inversion (day/year)	0.0314***	0.0400***	0.0028***	0.0036***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
KP F-statistics	78.7	536.91	12.19	174.33
Second stage				
SO_2 (μg/m³)	0.0571***	0.0618***	0.0558***	0.0523***
	(0.0174)	(0.0168)	(0.0189)	(0.0177)
Individual controls	NO	NO	YES	YES
Weather controls	NO	YES	NO	YES
Individual fixed effects	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
Observations	63,340	48,812	58,727	45,088

Table 6
2SLS result: using new thermal inversion variable as the instrument variable

	(1)	(2)	(3)	(4)
First stage				
Thermal inversion (110 m–540 m)	0.0113***	0.0040***	0.0104***	0.0030***
	(0.0008)	(0.0008)	(0.0008)	(0.0009)
KP F-statistics	222.37	2040.71	22.50	682.38
Second stage				
$PM_{2.5}$ (μg/m³)	0.0173***	0.0219	0.0207***	0.0224
	(0.0058)	(0.0207)	(0.0063)	(0.0267)
Individual controls	NO	NO	YES	YES
Weather controls	NO	YES	NO	YES
Individual fixed effects	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
Observations	63,340	48,812	58,727	45,088

Table 7
2SLS result: using individual height as the explanatory variable

	(1)	(2)	(3)	(4)
$PM_{2.5}$ (μg/m³)	0.0383	−0.0643	−0.0264	−0.1647
	(0.0805)	(0.1363)	(0.0890)	(0.1555)
Individual controls	NO	NO	YES	YES
Weather controls	NO	YES	NO	YES
Individual fixed effects	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES

Table 8
Heterogeneous analysis by gender

	Male (1)	Female (2)
$PM_{2.5}$ (μg/m³)	0.0553**	0.0137
	(0.0232)	(0.0099)
Individual controls	NO	NO
Weather controls	NO	YES
Individual fixed effects	YES	YES
Year fixed effects	YES	YES
Observations	23,351	21,718

Table 9
Heterogeneous analysis by education and household registration

	Education year		Household register type	
	<9 years (1)	≥9 years (2)	Rural (3)	Urban (4)
$PM_{2.5}$ (μg/m³)	0.0437**	0.0181	0.0468**	0.0085
	(0.0196)	(0.0113)	(0.0232)	(0.0067)
Individual controls	NO	NO	YES	YES
Weather controls	NO	YES	NO	YES
Individual fixed effects	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
Observations	23,428	20,394	24,546	19,528

the prevention, diagnosis, and treatment of respiratory diseases. For example, the spatial distribution of China's air quality shows a significant spatial clustering and divergence pattern, showing a spatial pattern of "heavy in the north and light in the south, heavy in the east and light in the west." The pollution level in Beijing, Tianjin, Hebei and surrounding areas is high; the southern coastal areas with the Pearl River Delta as the core, the Yunnan-Guizhou Plateau and the Qinghai-Tibet Plateau are perennial good areas.

Table 8 shows the results of IV estimation by subdividing the sample according to the gender of the respondents, indicating that men are more significantly affected by air pollution. The potential reason for this result is that men may work outdoors longer than women, so they are exposed to air pollutants longer.

Column 1 and column 2 of Table 9 present the regression results dividing respondents into two subsamples by education level. The education level of the respondents is determined by whether they had completed 9 years of compulsory education. The results show that the negative effect of air pollution is more significant for people with low education level. The reason may be that people with higher education levels are more sensitive to air pollution and are quicker to take protective measures, such as wearing masks or staying away from pollution sources, to protect their health and reduce the risk of obesity. In addition, we used household registration data from CFPS to divide the respondents into two subgroups: urban residents and rural residents. By comparing the data in column 3 and column 4, we find that the obesity level of rural residents is much more negatively affected by air pollution than that of urban residents. For rural residents, an increase in the average annual $PM_{2.5}$ concentration of 1 μg/m³ in the county significantly increased the risk of obesity by 0.0468, nearly double the baseline result.

5. Conclusion and policy implications

This study adopts 12,688 CFPS surveys as research samples, uses thermal inversion as an IV, and conducts a 2SLS regression to analyze the causal effect of air pollution on obesity risk. An increase of 1 μg/m³ of annual average $PM_{2.5}$ significantly increased the risk of obesity by 2.86%. In particular, the negative effects of air pollution were significant among people who are male, have low education, and live in rural areas.

The findings presented above provide the basis for three distinct policy recommendations aimed at mitigating air pollution and promoting public health.

First, air purification policies must be strengthened, whereby the government enforces emissions controls for industrial enterprises and transportation, promotes clean energy sources as a viable alternative to traditional ones, and limits the use of high-polluting vehicles. In addition, the establishment of green cities and green belts can improve urban air quality. The adoption of laws, regulations, economic incentives, and technological support can encourage businesses and individuals to reduce air pollution, which in turn reduces people's exposure to toxic pollutants, leading to a reduced risk of obesity.

Second, promoting healthy lifestyles is crucial in preventing obesity. The government can incentivize healthy living by introducing policies and measures that reduce the risk of obesity. One approach is through promoting urban planning and transportation policies that encourage walking, biking, or using public transportation to reduce motor vehicle use and increase physical activity. Furthermore, the government can foster participation in sports and outdoor activities by providing adequate public sports and fitness facilities to promote an active lifestyle.

Lastly, an effective approach to reducing obesity risk is through strengthening health education and awareness campaigns. By enhancing health education initiatives, the government can increase public understanding of the link between air pollution and obesity and provide guidance and behavioral advice for healthy living. This includes conducting extensive health education activities at schools, communities, and workplaces to raise public awareness of the health risks associated with air pollution and providing scientifically sound diet and lifestyle advice to promote better health management.

In conclusion, comprehensive policies that incorporate a range of strategies including government regulations, economic incentives, urban planning, and health education are essential for addressing air pollution, promoting healthy lifestyles, and reducing the risk of obesity. Implementation of these policies is expected to improve air quality and contribute to better public health outcomes.

Conflicts of Interest

Guanglai Zhang and Yayun Ren are editorial board members for *Green and Low-Carbon Economy*, and was not involved in the editorial review or the decision to publish this article. The authors declare that they have no conflicts of interest to this work.

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